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Mika Maliranta, Pierre Mohnen & Petri Rouvinen

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United Nations University - Maastricht Economic and social Research and training centre on Innovation and Technology
Keizer Karelplein 19, 6211 TC Maastricht, The Netherlands
Tel: (31) (43) 388 4400, Fax: (31) (43) 388 4499, e-mail: info@merit.unu.edu, URL: *http://www.merit.unu.edu*

Is Inter-Firm Labor Mobility a Channel of Knowledge Spillovers?
Evidence from a Linked Employer-Employee Panel

Mika Maliranta[1], Pierre Mohnen[2] & Petri Rouvinen[3]

Abstract
An employer-employee panel is used to study whether the movement of workers across firms is a channel of unintended diffusion of R&D-generated knowledge. Somewhat surprisingly, hiring workers from others' R&D labs to one's own does not seem to be a significant spillover channel. Hiring workers previously in R&D to one's non-R&D activities, however, boosts both productivity and profitability. This is interpreted as evidence that these workers transmit knowledge that can be readily copied and implemented without much additional R&D effort.

JEL codes: D62, J24, J62, L25, O31.
Keywords: Labor mobility, R&D spillovers, Profitability, Linked employer-employee data.

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[1] mika.maliranta@etla.fi, ETLA, The Research Institute of the Finnish Economy

[2] p.mohnen@merit.unimaas.nl, Maastricht University and UNU-MERIT

[3] petri.rouvinen@etla.fi, ETLA, The Research Institute of the Finnish Economy

Introduction

While it is commonly agreed that R&D generates positive externalities, because of rent and knowledge spillovers (for reviews see, e.g., Griliches, 1992; Mohnen, 1996), little is known about the channels of transmission through which they operate. Rent spillovers are most likely to occur via the trade of intermediate inputs and capital goods. Knowledge spillovers occur when information gets exchanged in a tacit or codified way when people meet, interact, trade, or cooperate, and is often measured by a proximity measure between emitter and receiver on the grounds that knowledge spillovers are more likely to happen when the two parties are similar and physically close to each other. Many proximity measures have been proposed, but very few studies are able to trace how spillovers actually make their way from one firm to the other. Following Arrow's (1962, p. 615) lead, it is nevertheless frequently suggested (see, e.g., Geroski, 1995; Stephan, 1996) that labor mobility – the movement of workers from one organization to another – is among the key transmission mechanisms of knowledge spillovers. Upon defining an agenda for future research (in the context of their critical survey of the literature on geographically localized knowledge spillovers), Breschi and Lissoni (2001, p. 1000) state that

> "The first entry in the agenda is the labour market… A crucial mechanism through which knowledge diffuses locally is the mobility of technologists and scientists, either across firms, and between firms and academic institutions."

This paper addresses the issue empirically by studying whether inter-firm labor mobility is a channel of knowledge spillovers, and whether they affect business performance. To this end a comprehensive longitudinal employer-employee panel dataset, available for research purposes at the Research Laboratory of Statistics Finland, is exploited.[1]

In our terminology knowledge spillovers occur when a firm's R&D project discloses new information that is useful to another firm in its R&D efforts, and the emitting firm is not fully compensated for the input. We make every effort to explicitly identify and isolate one potential channel of knowledge spillovers, namely inter-firm labor mobility. We device a setting where the potential spillovers may also be internalized by the labor market and where other factors possibly contributing to business performance are controlled for and other potential sources of bias are eliminated. Empirically we resort to long differences in studying firm-level profitability growth, and to an extent also productivity and average wage growth, with the shares of various types of hired, staying, and separating workers among the key variables of interest.

To anticipate our conclusions, we find that knowledge spillovers may be partly but are not fully internalized by the labor market. Thus, knowledge spillovers exist, albeit not necessarily of the most obvious type. Perhaps surprisingly, hiring workers from others' R&D labs to one's own does not seem to be a statistically significant spillover channel, even if we find weak support for it. Hiring workers previously in R&D to one's non-R&D activities, however, clearly boosts both productivity and profitability. This is interpreted as evidence that these workers transmit knowledge that can be readily copied and implemented without much additional R&D effort. Our paper makes a contribution to the scarce literature that explicitly studies how spillovers come about and how they are being transmitted.

Section 2 briefly reviews the previous literature on the topic. The model to be estimated is derived in Section 3. Section 4 discusses the employed data and its properties. Section 5 presents the baseline results, the robustness of which is discussed in Section 6. Section 7 concludes.

1. Literature

This section reviews the theoretical and empirical studies that explicitly consider inter-firm labor mobility as a channel of knowledge spillovers.

Cooper (2001) sets up a theoretical two-period competitive industry model, where labor mobility is the vehicle diffusing knowledge from one firm to another, and where R&D and labor mobility are determined endogenously. The model emphasizes the duplicative nature of R&D; both the previous and the current employer of a job switcher utilize the same knowledge simultaneously. It is shown that higher mobility does not necessarily reduce R&D investment and that it generally promotes productivity growth. Due to the opposing external effects of emitting and absorbing spillovers, an efficient labor mobility outcome can be reached despite apparent incentive problems. Fosfuri and Rønde (2004) present a game-theoretic model of labor mobility with a particular emphasis on cumulative innovations. In their model a firm hires a researcher to conduct R&D, which gives rise to knowledge valuable for both direct commercialization (first generation) and as a basis for further innovations (second generation). After a first generation success a researcher can move to a rival and use the previous employer's knowledge to come up with a second generation innovation. As workers are mobile, especially within their current region, firms' have a choice of either clustering with or isolating themselves from other firms with consequences on industry-level knowledge spillovers. It is found that firms' incentives to cluster are the strongest when (1) the value of the second generation is high relative to the first (high benefits of hiring from rivals), (2) competition in the product market is soft (loosing workers to rivals does not have severe end-market effects), and (3) the probability of a single firm developing an innovation is relatively low. In industries where clustering is driven by spillovers, both labor mobility and wages of skilled workers are high. Kim and Marschke (2005) model the effects of scientists' mobility on firms' R&D and patenting decisions. They emphasize the role of patenting in protecting firms' intellectual assets from (former) employees. The threat of an employee departing from a firm has two effects: it reduces the firm's R&D expenditures, as a scientist is willing to indirectly pay (by accepting a lower wage) for the possible external return on the knowledge acquired through R&D, and it raises the propensity to patent, as the firm protects itself against the possibility of departing employees. The empirical findings with firm-level panel data confirm the latter result. Scientists' mobility is associated with variations in cross-industry and increases in economy-wide patenting. Franco and Filson (2006) device a model in which knowledge diffuses when employees are able to imitate their employer's technology. The former employees may use it to create competing firms (spin-outs). Employers adjust current wages downward to reflect the value of imitating until a Pareto optimal equilibrium is reached. In the competitive equilibrium mobility nevertheless remains socially suboptimal. More advanced parent firms are more likely to spawn spin-outs. The model's implications are found to hold in the rigid disk drive industry. Combes and Duranton (2006) study the trade-offs in clustering with a rival firm in a game of two firms with differentiated products. They focus on the intensity of competition in both the product and the labor markets. A continuum of workers and reciprocal labor mobility are among the key features of their model. It is assumed that labor and knowledge flows coincide. It is found that generally firms choose to co-locate. As competition intensifies, labor flows are reduced as firms raise the wages of their most strategic workers thereby increasing the costs (wages) and lowering the benefits (knowledge flows) of co-location. When conditions of perfect competitions are approached, firms choose to separate. Firms' productivity and its growth is predicted to increase with equilibrium labor mobility.

On the empirical side, Almeida and Kogut (1999) study inter-firm mobility of major patent holders. They find that mobility of scientists indeed influences local transfer of knowledge. In certain cases (particularly Silicon Valley) knowledge seems to be geographically localized and embedded in regional labor networks. Power and Lundmark (2004) suggest that, rather than flowing in-the-air or being exchanged via informal and accidental encounters, knowledge is developed and diffused through work-related interactions. Thus, labor mobility is among the most likely ways of knowledge transfer. It may work through three major channels: by speeding up knowledge dissemination and learning processes, by creating new combinations of knowledge embodied in people, as well as by bonding and linking firms, workplaces, and institutions. The issue is studied with individual-level panel data of the ICT concentration in the Stockholm region. Individuals specializing into particular sub-sectors have higher mobility rates. There is indirect evidence that the observed relatively high mobility rate within the ICT sector promotes industrial concentration and firm performance. Møen (2005) studies the mobility of technical staff as a channel of R&D spillovers using employer–employee data in 1986–95 covering roughly 30,000 workers in 750 plants in the Norwegian machinery and equipment industry. He insists that R&D, the primary and specific purpose of which is to come up with new product and process ideas (inventions) and designs, is also a learning process for those involved. Thus, while the firm's decision to invest in R&D is motivated by potential future profits, due to appropriability problems an employee might earn returns on the firm's investment. Møen's key proposition – stemming from the classical human capital theory (Becker, 1962; Mincer, 1958) – is that to the extent that employees receive on-the-job training, they should be willing to pay for it in anticipation of higher wages in the future. He constructs and estimates various wage models with R&D-related experience profiles among the key variables of interest. It is indeed found that technical staff in R&D-intensive firms have lower wages early in their careers and later earn returns on their implicit investment in the form of higher wages. "These findings suggest that the potential externalities associated with labor mobility, at least to some extent, are internalized in the labor market." (Møen, 2005, p. 83). Magnani (2006) replicates and extends Møen's (2005) investigation with a panel of US manufacturing workers and two-digit industry-level R&D intensities. Magnani's results provide some support to Møen's findings: also in the US there seems to be a R&D-induced steepening of the wage profile; there is, however, little evidence for an earnings drop in R&D-intensive industries at early stages of one's career. As pointed out by the author, the latter (non-)finding might be driven by the use of industry-level R&D, as opposed to the firm-level R&D data used by Møen. Fallick, Fleischman, and Rebitzer (2006) consider inter-firm labor mobility as a possible source of agglomeration economies with a panel of college-educated male employees in twenty US metropolitan areas with computer industry agglomerations. The findings suggest that high mobility in the computer industry facilitates reallocation of resources in the Silicon Valley. As compared to other locations in the US, mobility and related agglomeration economies seem to be more pronounced in California, where a state law makes non-compete agreements unenforceable. The heightened mobility is not to be found in other Californian industries, lending support to the authors' hypothesis that the external economies of scale are particularly important in industries with modular innovation.

2. MODEL

Our model employs a variant of a micro-level productivity decomposition method (cf. Ilmakunnas and Maliranta, 2005, 2007).[2] With linked employer-employee data it is possible to study the profitability, productivity, and wage effects of hired, staying, and separating workers by their type. Ilmakunnas and Maliranta (2005, 2007) focus on the role of age. The proposed extension tracks the nature of the employees' job assignments – whether in R&D or non-R&D tasks – before and after a job change.

A firm's labor force consists of different worker groups $j = 1,...,M$. The firm's output (value added) in period 1 is defined as the sum of the outputs of the worker groups (defined by, e.g., age, education, and/or employee tenure):

$$Y_1 = \sum_j Y_{1j} \ . \tag{1}$$

The firm's labor productivity is the labor share weighted average of the groups' labor productivities:

$$\frac{Y_1}{L_1} = \sum_j \frac{L_{1j}}{L_1} \frac{Y_{1j}}{L_{1j}}. \tag{2}$$

Each worker group can further be divided into two subgroups: workers who were employed by the firm at the previous period 0, i.e., staying workers (*stay*), and those who were not, i.e., hired workers (*hire*). Thus, the firm's labor productivity becomes

$$\frac{Y_1}{L_1} = \sum_j \frac{L_{1j,stay}}{L_1} \frac{Y_{1j,stay}}{L_{1j,stay}} + \sum_j \frac{L_{1j,hire}}{L_1} \frac{Y_{1j,hire}}{L_{1j,hire}}. \tag{3}$$

Because the labor shares must add up to one

$$\sum_j \frac{L_{1j,stay}}{L_1} + \sum_j \frac{L_{1j,hire}}{L_1} = 1, \tag{4}$$

after some manipulations (as shown in the appendix), equation (3) can be re-written as follows:

$$\frac{Y_1}{L_1} = \sum_j^M \frac{L_{1j,stay}}{\sum_j L_{1j,stay}} \frac{Y_{1j,stay}}{L_{1j,stay}} + \sum_j^M \frac{L_{1j,hire}}{L_1} \left(\frac{Y_{1j,hire}}{L_{1j,hire}} - \frac{Y_{1,stay}}{L_{1,stay}}\right). \tag{5}$$

where $Y_{1,stay} = \sum_j Y_{ij,stay}$ and $L_{1,stay} = \sum_j L_{ij,stay}$.

In period 0 we have to separate out the workers who will remain with the firm in period 1 and those who will not, i.e., the separating workers (*sepa*). Noting that

$$\sum_j \frac{L_{0j,stay}}{L_0} + \sum_j \frac{L_{0j,hire}}{L_0} = 1 \tag{6}$$

the firm's labor productivity in period 0 is

$$\frac{Y_0}{L_0} = \sum_j^M \frac{L_{0j,stay}}{\sum_j L_{0j,stay}} \frac{Y_{0j,stay}}{L_{0j,stay}} + \sum_j^M \frac{L_{0j,sepa}}{L_0} \left(\frac{Y_{0j,sepa}}{L_{0j,sepa}} - \frac{Y_{0,stay}}{L_{0,stay}}\right). \tag{7}$$

By definition the staying workers in period 0 and in period 1 are the same individuals. Assuming that they are in the same group, we have:

$$L_{0j,stay} = L_{1j,stay}. \tag{8}$$

The difference of period 0 and 1 productivity levels is

$$\Delta \frac{Y}{L} = \frac{Y_1}{L_1} - \frac{Y_0}{L_0} \tag{9}$$

Slight manipulation yields

$$
\begin{aligned}
&\frac{Y_1}{L_1}-\frac{Y_0}{L_0}= \\
&\sum_j \frac{L_{0j,stay}}{\sum_j L_{0j,stay}}\left(\frac{Y_{1j,stay}}{L_{1j,stay}}-\frac{Y_{0j,stay}}{L_{0j,stay}}\right)+ \\
&\sum_j \frac{L_{1j,hire}}{L_1}\left(\frac{Y_{1j,hire}}{L_{1j,hire}}-\frac{Y_{1,stay}}{L_{1,stay}}\right)+ \\
&\sum_j \frac{L_{0j,sepa}}{L_0}\left(\frac{Y_{0,stay}}{L_{0,stay}}-\frac{Y_{0j,sepa}}{L_{0j,sepa}}\right)
\end{aligned}
. \tag{10}
$$

The first term on the right-hand side of Equation (10) captures the firm's labor productivity change attributable to the staying workers. It is the labor share weighted average of the productivity changes across worker groups. It may be interpreted as productivity growth due to the accumulation of human capital through experience. These workers may have such human capital that enables them to adopt or come up with more productive techniques, i.e., these workers may have dynamic long-run effects on the firm's productivity.[3]

The second term on the right-hand side of Equation (10) captures the firm's labor productivity change attributable to hiring new workers. Hiring workers in group j boosts productivity, if the hires have on average a higher productivity level than the stayers in period 1. New hires may be more productive, e.g., due to skills, competences, and knowledge acquired in previous employment. Hiring-related adjustment costs are implicitly included, i.e., the new hires relative productivity is net of adjustment costs.

Finally, the third term on the right-hand side of Equation (10) captures the firm's labor productivity change attributable to separating workers. Separating workers in group j boosts productivity, if they have a lower productivity level than the average stayer in period 0.

We parameterize productivity of hired, separated, and staying workers assuming them to be constant within worker groups. Other differences across firms are captured by the variables contained in vector $\mathbf{Z}$. The remaining unexplained deviations ε are considered white noise.

Besides labor productivity, a similar decomposition can be used for the firm's average wage level by simply substituting W for Y. Thus, the following equations can be specified:

$$
\frac{\Delta(Y/L)}{\overline{(Y/L)}}=\alpha+\sum_j \beta_{(Y/L),j,hire}HR_j+\sum_j \beta_{(Y/L),j,sepa}SR_j+\sum_j^{M-1}\chi_{(Y/L),j,stay}STAYSH_j+\delta'\mathbf{Z}_j+\varepsilon, \tag{11}
$$

$$\frac{\Delta(W/L)}{\overline{(W/L)}} = \alpha + \sum_j \beta_{(W/L),j,hire} HR_j + \sum_j \beta_{(W/L),j,sepa} SR_j + \sum_j^{M-1} \chi_{(W/L),j,stay} STAYSH_j + \delta' \mathbf{Z}_j + \varepsilon, \quad (12)$$

where $\overline{(Y/L)} = 0.5\left[(Y_0/L_0)+(Y_1/L_1)\right]$ and $\overline{(W/L)} = 0.5\left[(W_0/L_0)+(W_1/L_1)\right]$ are the average productivity and wage levels, $HR_j = \frac{L_{1j,hire}}{L_1}$ and $SR_j = \frac{L_{0j,sepa}}{L_0}$ are the hiring and separating rates, and $STAYSH_j = \frac{L_{0j,stay}}{\sum_j L_{0j,stay}}$ is the share of staying workers.

The labor productivity effects of hiring and separating workers in group j is thus

$$\beta_{(Y/L),j,hire} = \frac{(Y/L)_{1,j,hire} - (Y/L)_{1,stay}}{\overline{(Y/L)}} \text{ and} \quad (13)$$

$$\beta_{(Y/L),j,sepa} = \frac{(Y/L)_{0,stay} - (Y/L)_{0,j,sepa}}{\overline{(Y/L)}} \quad . \quad (14)$$

Intercept α indicates the growth rate in the reference group of stayers. Thus, $\chi_{(Y/L),j,stay}$ indicates the growth rate difference between group j and the reference group.

Firms are ultimately interested in profitability, which for the present purposes is defined as follows (see Ilmakunnas and Maliranta, 2007):

$$\Pi = 1 + \frac{OPM}{W(1+a)} = \frac{Y}{W(1+a)} = \frac{Y/L}{(1+a)(W/L)}, \quad (15)$$

where OPM denotes the operating margin $OPM = Y - W(1+a)$, where a is the ratio of payroll taxes to wages assumed to be constant over time and across worker groups.[4] The growth rate of profitability is thus simply the difference between the growth rates of productivity and wages, which is approximated by

$$\frac{\Delta\Pi}{\overline{\Pi}} \cong \frac{\Delta(Y/L)}{\overline{(Y/L)}} - \frac{\Delta(W/L)}{\overline{(W/L)}} \quad , \quad (16)$$

where $\overline{\Pi} = 0.5\left[\Pi_0 + \Pi_1\right]$. We then obtain the profitability equation

$$\frac{\Delta\Pi}{\overline{\Pi}} = \alpha + \sum_j \beta_{\Pi,j,hire} HR_j + \sum_j \beta_{\Pi,j,sepa} SR_j + \sum_j^{M-1} \chi_{\Pi,j,stay} STAYSH_j + \delta' \mathbf{Z}_j + \varepsilon, \quad (17)$$

where, on the basis of (14), the following approximations hold

$$\beta_{\Pi,j,hire} \approx \beta_{(Y/L),j,hire} - \beta_{(W/L),j,hire} \text{ and} \quad (18)$$

$$\beta_{\Pi,j,sepa} \approx \beta_{(Y/L),j,sepa} - \beta_{(W/L),j,sepa} \, . \quad (19)$$

Since

$$\beta_{(Y/L),j,hire} = \frac{(Y/L)_{1,j,hire} - (Y/L)_{1,stay}}{\overline{(Y/L)}} \approx \ln \frac{(Y/L)_{1,j,hire}}{(Y/L)_{1,stay}} \tag{20}$$

and

$$\beta_{(W/L),j,hire} = \frac{(W/L)_{1,j,hire} - (W/L)_{1,stay}}{\overline{(W/L)}} \approx \ln \frac{(W/L)_{1,j,hire}}{(W/L)_{1,stay}}, \tag{21}$$

we can write

$$\begin{aligned} &\beta_{\Pi,j,hire} \approx \ln \frac{(Y/L)_{1,j,hire}}{(Y/L)_{1,stay}} - \ln \frac{(W/L)_{1,j,hire}}{(W/L)_{1,stay}} = \ln \frac{(Y/W)_{1,j,hire}}{(Y/W)_{1,stay}} \\ &\Leftrightarrow \beta_{\Pi,j,hire} \approx \ln \frac{\Pi_{1,j,hire}}{\Pi_{1,stay}} \end{aligned}, \tag{22}$$

which shows that the parameter of the hiring variable for the worker group j in the profit equation (14) can be interpreted as a measure of the profitability level of the hired group j workers relative to all stayers in period 1.

Analogously, we obtain that

$$\beta_{\Pi,j,sepa} \approx \ln \frac{\Pi_{0,j,sepa}}{\Pi_{0,stay}}, \tag{23}$$

which provides us a measure of the relative profitability level of the separated group j workers before they leave.

There are three main sources of bias when analyzing firm performance and labor characteristics empirically. First, there may be unobservable firm heterogeneity both in productivity and wage levels, which is correlated with the firms' choice of labor input. For example, the firm vintage and worker cohorts tend to be tied together, with young workers being employed in firms that have new equipment and high productivity levels. Since we are using growth rates as the dependent variables, this is not an issue of great concern here. That is, if there is an unobserved firm-specific time-invariant component in the productivity or average wage level, it is eliminated in the rates of change. Our approach is related to the use of long differences (see, e.g., Griliches and Mairesse, 1998); we define the growth rates and labor flows in a five-year window. We also control for some observable firm characteristics, included in $\boldsymbol{Z}$ (see below).

Second, there is heterogeneity across workers. This would not be an issue if the firms randomly chose new employees from the pool of applicants or randomly picked up those who are laid off. This is not likely to be the case, however, since the firms attempt to hire the best and lay-off the poorest performers. The hiring and separating flows may therefore be unrepresentative with respect to the corresponding groups in the whole population. However, since the selection bias is likely to affect the productivity and wage growth rates in the same way (see Hellerstein and Neumark, 2004), it should at least be eliminated when examining their difference, i.e. the growth rate in profitability.

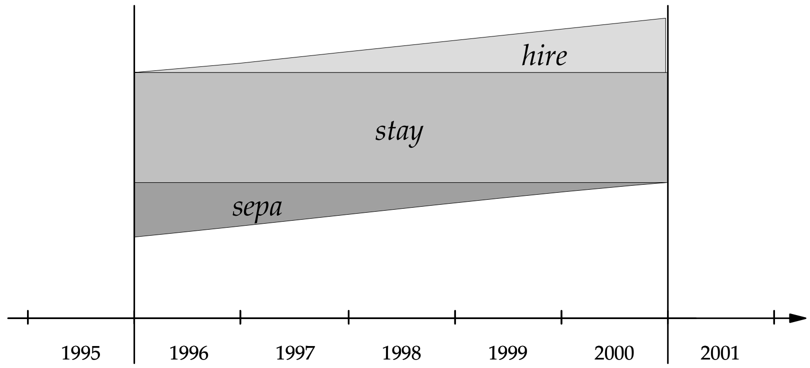
Third, the hiring and separation rates are based on the firms' decisions and are thus possibly correlated with the error term. This simultaneity problem may be most pronounced for inputs that are most adjustable (Marschak and Andrews, 1944). For example, positive technology shock may lead to the hiring of new, young workers, which then causes an overestimate of their productivity effect (cf. Levinsohn and Petrin, 2003; Olley and Pakes, 1996). Ilmakunnas and Maliranta (2007) used regional employment variables as instruments when studying the productivity effects by age groups. This robustness check did not challenge their main conclusions. Due to data constraints a similar instrumental variable approach is not feasible here.[5] From the point of view of this paper an important question is whether a positive shock increases a firm's propensity to hire R&D workers.[6]

3. DATA

The data for this study is drawn from the *Finnish Longitudinal Employer–Employee Data* (FLEED) publicly available for research purposes (subject to terms and conditions of confidentiality) at *Statistics Finland*'s research laboratory. FLEED merges comprehensive taxation and other administrative records of <u>all labor force members</u> as well as <u>all employers/enterprises</u> subject to value added tax (VAT); it can be complemented by a range of additional information from both private and public sources.[7]

Figure 1 illustrates the empirical setup. The linked employees and their characteristics are observed at the end of the year 1995 and 2000. These two points in time are compared to determine the categories of staying, hiring and separating workers.[8]

Figure 1. The empirical setup.



Hiring, staying, and separating are considered across five characteristics of the individuals in the respective categories (the composition of each group is determined by the symbols in the middle columns of Table 1):

the age of the workers (either ***Y**oung* or ***O**ld*, with those being 35 years or less in the initial period defined as being ***Y**oung*),

the educational level of the workers (either ***L**ower* or ***H**igher*, the latter group composed of all those having at least a bachelor's or equivalent degree),

the tenure of the workers in the firm (either ***S**hort* or ***L**ong ten.*, those that in the initial period had been with the firm 5 years or less being defined as having ***S**hort* tenure),

the previous job assignment (having been employed elsewhere either in *R&D* or in *Other* (non-R&D) activities, as well as

the current job assignment (being employed in the firm either in *R&D* or in *Other* activities).[9]

R&D workers are defined as those in the group of "senior officials and employees in research and planning".[10] As shown in Table 1, this categorization leads us to consider a total of 28 hiring, staying, and separating shares.[11]

Table 1. Variable definitions.

Labor mobility variables	Young/Old	Lower/Higher ed.	Short/Long ten.	R&D/Oth., prev.	R&D/Oth., curr.	Description (*Hire* -variables are shares of end-year total employment; *Stay* -variables are shares of continued employment (start-year = end-year); *Sepa* -variables are shares of start-year employment)
Hire, Young into Other	Y	L	S	O	O	Hired young/low-ed., prev. & curr. in non-R&D
Hire, Old into Other	O	L	S	O	O	Hired old/low-ed., prev. & curr. in non-R&D
Hire, Young/Ed. into Other	Y	H	S	O	O	Hired young/hi-ed., prev. & curr. in non-R&D
Hire, Old/Ed. into Other	O	H	S	O	O	Hired old/hi-ed., prev. & curr. in non-R&D
Hire, Young/R&D into Other	Y	H	S	R	O	Hired young, prev. in R&D & curr. in non-R&D
Hire, Old/R&D into Other	O	H	S	R	O	Hired old, prev. in R&D & curr. in non-R&D
Hire, Young/R&D into R&D	Y	H	S	R	R	Hired young, prev. & curr. in R&D
Hire, Old/R&D into R&D	O	H	S	R	R	Hired old, prev. & curr. in R&D
Hire, Young/Ed. into R&D	Y	H	S	O	R	Hired young, prev. in non-R&D & curr. in R&D
Hire, Old/Ed. into R&D	O	H	S	O	R	Hired old, prev. in non-R&D & curr. in R&D
Stay, Young in Other	Y	L	S	O	O	Stayed young/low-ed. w. short ten. in non-R&D
Stay, Old in Other	O	L	S	O	O	Stayed old/low-ed. w. short ten. in non-R&D
Stay, Old/Ten. in Other	O	L	L	O	O	Stayed old/low-ed. w. long ten. in non-R&D
Stay, Young/Ed. in Other	Y	H	S	O	O	Stayed young/hi-ed. w. short ten. in non-R&D
Stay, Old/Ed. in Other	O	H	S	O	O	Stayed old/hi-ed. w. short ten. in non-R&D
Stay, Old/Ed./Ten. in Other	O	H	L	O	O	Stayed old/hi-ed. w. long ten. in non-R&D
Stay, Young in R&D	Y	H	S	R	R	Stayed young/hi-ed. w. short ten. in R&D
Stay, Old in R&D	O	H	S	R	R	Stayed old/hi-ed. w. short ten. in R&D
Stay, Old/Ten. in R&D	O	H	L	R	R	Stayed old/hi ed. with long tenure in R&D jobs
Sepa, Young from Other	Y	L	S	O		Sep. young/low-ed. w. short ten. in non-R&D
Sepa, Old from Other	O	L	S	O		Sep. old/low-ed. w. short ten. in non-R&D
Sepa, Old/Ten. from Other	O	L	L	O		Sep. old/low-ed. w. long ten. in non-R&D
Sepa, Young/Ed. from Other	Y	H	S	O		Sep. young/hi-ed. w. short ten. in non-R&D
Sepa, Old/Ed. from Other	O	H	S	O		Sep. old/hi-ed. w. short ten. in non-R&D
Sepa, Old/Ed./Ten. from Other	O	H	L	O		Sep. old/hi-ed. w. long ten. in non-R&D jobs
Sepa, Young from R&D	Y	H	S	R		Sep. young/hi-ed. with short ten. in R&D
Sepa, Old from R&D	O	H	S	R		Sep. old/hi-ed. w. short ten. in R&D
Sepa, Old/Ten. from R&D	O	H	L	R		Sep. old/hi-ed. w. long ten. in R&D

Other variables	Description
Labor productivity growth	Start- & end-year diff. of value added / worker / its start- & end-year avg.
Average wage growth	Start- & end-year diff. of average wage / its start- & end-year avg.
Profitability growth	Start- & end-year diff. / its start- & end-year avg. (see the text)
Industry	Dummies: two-digit NACE rev. 1 industries (41 in all)
Region	Dummies: two-digit NUTS regions (20 in all)
Firm age	Log of firm age
Multi-establishment	The firm has multiple establishments
Foreign ownership	Dummy: Foreign ownership (≥ 20%) at the beginning/end period.
Initial labor productivity	Log of initial period labor productivity level
Initial wage sum	Log of initial average wage
Capital intensity growth	Start- & end-year log-diff. of the (physical) capital/labor ratio

As the model derived in the previous section suggests, the *hiring* variables are defined as shares of end-year total employment, the *staying* variables as shares of continued employment,[12] and the *separating* variables as shares of start-year employment. The worker groups are mutually exclusive: thus, the *hiring* variables add up to the overall hiring rate, the *staying* variables add up to one, and the *separating* variables add up to the overall separation rate.

Four variables in Table 1 – namely *Hire, Young/R&D into Other*; *Hire, Old/R&D into Other*; *Hire, Young/R&D into R&D*; and *Hire, Old/R&D into R&D* – are the keys in answering the question whether inter-firm labor mobility is a channel of knowledge spillovers. To the extent that knowledge spillovers are internalized by the labor market, they are subtracted from the main dependent variable of profitability growth. If, however, there are economically significant (i.e., influencing business performance) un-internalized spillovers from other firms' R&D, they should show up in these four variables. The argument is that to the extent that wages do not fully reflect personal productivities of respective workers, acknowledging the fact that s/he comes from another firm's R&D lab should capture the possible transfer of the knowledge accumulated via the stream of the other firm's R&D investments. Thus, these variables should capture the equivalent of 'stealing blueprints' upon leaving for a new job, although it is by no means necessary (or common to our understanding) that such spillover should ever take illegal or immoral forms.

Besides considering the issue separately for younger and older workers, also note that the personnel previously engaged in R&D is also split into those having new assignments in either R&D or other activities. While both of these groups can potentially spill over the R&D-generated knowledge of previous employers, arguably the transferred knowledge may be of a different type: it seems plausible that a former R&D engineer is hired to non-R&D activities, because the spilloverable knowledge s/he possesses can be implemented so readily that it is unnecessary to funnel it through the receiving firm's R&D lab. Knowledge being channeled through the lab (by rather having a job assignment there) might be also relevant, but perhaps not as readily implementable upon being hired.

Firms' *outputs* and *inputs* are observed during the one-year periods immediately following the two points in time when employment and its characteristics are observed. The growth rates in performance are then calculated by subtracting the performance levels in the two time periods (1996 and 2001) and then dividing them by their mid-year values, as discussed in the previous section.[13]

Even if time-invariant firm effects are removed by construction from the dependent variables when considering growth rates, we include a fairly extensive set of controls in order to capture possible differences in dynamics across time. Industry dummies (NACE rev. 1 two-digit industries, 41 in all) account for the effects of idiosyncratic industry shocks; likewise a set of dummies controls for the possible regional effects (NUTS two-digit regions, 20 in all). The (log of) age of the firm is controlled for. A dummy captures the firm's exposure to foreign ownership. A dummy indicating that the firm has multiple establishments is also included. Changes in capital structure are controlled for by the log-difference of the start- and end-year physical capital intensity. In order to capture the possible catching-up or life cycle effects in productivity dynamics, the start-year levels of labor productivity and average wage are also included as controls.[14]

Observations are lost from our sample for various reasons. Our approach dictates that we must focus on those firms that appear in both the initial and the end year.[15] In addition, we have required that at least 10 persons can be linked to the firm in both years. Some observations are dropped from the analysis due to missing information.[16]

Before conducting the econometric analysis we leave out some potentially erroneous observations that might distort our results. First, we remove those observations where the number of linked employees differs by more than 10% from the number of employees in the company data, as this indicates that the linking of the individual and firm data is incomplete. Second, we remove some potentially influential outliers that we identified by using the method proposed by Hadi (1992, 1994).[17] In the baseline estimations we include firms that employ at least 20 persons. The main reason for leaving the smaller firms out is that the employment numbers of them are sometimes imputed on the basis of wages, which could badly distort the analysis in our setting.

Finally we are left with an estimation sample of 1,339 firms (with some 200,000 employees) for our baseline estimation. The sample covers about one third of the corresponding population of firms and persons.

Table 2 presents descriptive statistics of the sample. In order to protect the identities of the firms included in the data, we report the 1st and 99th percentile values rather than the more usual minimum and maximum values. In the course of the five-year window considered, new hires account for 34.6% (= sum of the *Hire* variables) of the end-of-window employment. Of these, 84.5% are lower educated (i.e., non-university) "production" (i.e., non-R&D) workers (*Hire, Young into Other* and *Hire, Old into Other*); new R&D hires were 6.1% of the total. 88.4% of the stayers were lower education production workers (the sum of *Stay, Young in Other*, *Stay, Old in Other*, and *Stay, Old/Ten. in Other*); also among stayers those in R&D accounted for 6.1% of the total. In the course of the five-year window, the separation rate (= sum of the *Sepa* variables; those departed between the two comparison points in ratio to the initial employment) is 40.2%, of which 88.2% of these are lower educated production and 5.2% R&D workers. Labor productivity (in nominal terms) grew at an average compound annual growth rate of about 10 %, the average wage 13 %, and profitability -1.2% a year.

The average productivity, i.e., value added per person, is 54,800 euros in 2001. The average wage level, i.e., wages per person, is 28,000 euros, which means 2,350 euros per month.[18] A comparison with the official statistics suggest that our sample is quite representative: The average value added per person in these industries was 56,700 thousands euros in 2001 (Structural Business Statistics, Eurostat). The average monthly earnings of the full-time workers in industry and services were 2,380 euros in 2001 (Gross Earnings Statistics, Eurostat).

Table 2. Descriptive statistics of the baseline estimation sample.

Variables	Unit	Mean	Percentiles				
			1st	25th	50th	75th	99th
Hire, Young into Other	%	20.5	0.0	3.0	17.7	46.8	65.8
Hire, Old into Other	%	8.7	0.0	0.0	6.9	25.0	39.1
Hire, Young/Ed. into Other	%	2.2	0.0	0.0	0.4	9.5	19.4
Hire, Old/Ed. into Other	%	0.8	0.0	0.0	0.0	4.3	9.1
Hire, Young/R&D into Other	%	0.2	0.0	0.0	0.0	1.3	3.7
Hire, Old/R&D into Other	%	0.1	0.0	0.0	0.0	0.6	2.9
Hire, Young/R&D into R&D	%	0.4	0.0	0.0	0.0	2.9	5.4
Hire, Old/R&D into R&D	%	0.2	0.0	0.0	0.0	1.5	5.0
Hire, Young/Ed. into R&D	%	1.1	0.0	0.0	0.0	5.4	15.8
Hire, Old/Ed. into R&D	%	0.4	0.0	0.0	0.0	2.3	5.9
Stay, Young in Other	%	31.5	0.0	7.1	29.4	63.4	79.6
Stay, Old in Other	%	4.5	0.0	0.0	1.2	16.7	54.2
Stay, Old/Ten. in Other	%	52.4	0.0	12.9	56.1	80.0	89.5
Stay, Young/Ed. in Other	%	1.5	0.0	0.0	0.0	7.7	17.6
Stay, Old/Ed. in Other	%	0.2	0.0	0.0	0.0	0.9	6.8
Stay, Old/Ed./Ten. in Other	%	3.8	0.0	0.0	1.0	15.8	28.3
Stay, Young in R&D	%	2.1	0.0	0.0	0.0	10.0	31.3
Stay, Old in R&D	%	0.4	0.0	0.0	0.0	1.9	7.2
Stay, Old/Ten. in R&D	%	3.6	0.0	0.0	0.0	16.7	44.6
Sepa, Young from Other	%	17.1	0.0	2.5	14.3	41.3	65.2
Sepa, Old from Other	%	2.9	0.0	0.0	1.2	12.0	24.2
Sepa, Old/Ten. from Other	%	15.4	0.0	0.0	13.8	34.8	46.8
Sepa, Young/Ed. from Other	%	1.1	0.0	0.0	0.0	5.0	11.1
Sepa, Old/Ed. from Other	%	0.3	0.0	0.0	0.0	2.2	4.8
Sepa, Old/Ed./Ten. from Other	%	1.3	0.0	0.0	0.0	6.5	12.5
Sepa, Young from R&D	%	1.1	0.0	0.0	0.0	5.9	14.5
Sepa, Old from R&D	%	0.2	0.0	0.0	0.0	1.4	4.8
Sepa, Old/Ten. from R&D	%	0.7	0.0	0.0	0.0	4.2	8.5
Labor productivity growth	%	10.4	-84.1	-42.7	10.9	61.6	90.8
Average wage growth	%	13.4	-39.8	-19.5	15.5	36.2	55.5
Profitability growth	%	-1.2	-88.5	-44.1	-1.1	43.0	67.9
Capital intensity growth	%	5.9	-231.8	-102.8	5.2	119.8	211.2

4. RESULTS

Table 3 presents White (1980) heteroscedasticity-consistent ordinary least squares (OLS) estimates of the model derived in Section 3. These are our baseline results that are estimated with weighting by firm size (the average of the initial and the last year's employment). A justification for using weighting comes from the fact that we are interested in the profitability and productivity effects of the employment flows. Unweighted estimation gives equal weight to large firms with low flow rates and small firms that have high flow rates but account for a small share of employment. Another justification for using employment weights is that the errors are likely to be heteroscedastic in a way that standard deviations are inversely proportional to firm size (Ilmakunnas and Maliranta, 2005). The left-most column shows the regression with the profitability growth as the dependent variable and thus provides our core set of results. The middle column shows a regression with the labor productivity growth as the dependent variable.[19] The right-most column shows a regression with the average wage growth as the dependent variable. Note that for many independent variables the left-most column is the difference between the middle and the right-most column, although the correspondence is just approximate.

We first briefly comment on the variables other than those related to labor mobility: As expected, growth of capital intensity increases productivity. The employees also seem to benefit from investments in the form of increased wages. The initial labor productivity level is negatively related to profitability and productivity growth indicating a catching-up or regression-towards-mean phenomenon (Friedman, 1992). Its relation to wage growth is, however, positive. One explanation for this finding is that the employees are rewarded for the employer's performance via profit-sharing and similar schemes. The average initial wage level is negatively associated with wage growth. Interestingly, its relationship with profitability growth is positive. Foreign-owned companies have higher growth rates of profitability, productivity and wage than domestically-owned ones, but only the coefficient for wage growth is statistically significant. Consistently with various firm's life-cycle models, older firms have lower productivity growth. However, the same holds true for wage growth, leaving the profitability growth effect statistically insignificant.

Table 3. The baseline regression results.

		Profitability	*Productivity*	*Wage*
(1)	*Hire, Young into Other*	-0.063	-0.087	-0.028
		(0.106)	(0.118)	(0.060)
(2)	*Hire, Old into Other*	-0.204	-0.367 **	-0.163 **
		(0.177)	(0.178)	(0.068)
(3)	*Hire, Young/Ed. into Other*	0.690 *	0.929 **	0.410 **
		(0.404)	(0.402)	(0.184)
(4)	*Hire, Old/Ed. into Other*	-0.656	-0.392	0.516
		(0.701)	(0.761)	(0.347)
(5)	*Hire, Young/R&D into Other*	3.922 **	4.469 **	0.574
		(1.888)	(2.122)	(0.847)
(6)	*Hire, Old/R&D into Other*	4.498 **	5.236 **	1.295
		(2.189)	(2.512)	(0.853)
(7)	*Hire, Young/R&D into R&D*	-1.512	-0.709	0.674
		(1.369)	(1.386)	(0.450)
(8)	*Hire, Old/R&D into R&D*	1.946	1.687	-0.037
		(1.329)	(1.424)	(0.586)
(9)	*Hire, Young/Ed. into R&D*	-0.427	-0.533	0.154
		(0.547)	(0.625)	(0.252)
(10)	*Hire, Old/Ed. into R&D*	-0.303	-0.424	-0.190
		(0.719)	(0.784)	(0.347)
(11)	*Stay, Old in Other*	-0.111	-0.411 **	-0.266 ***
		(0.136)	(0.164)	(0.078)
(12)	*Stay, Old/Ten. in Other*	0.026	-0.021	-0.114 **
		(0.099)	(0.102)	(0.047)
(13)	*Stay, Young/Ed. in Other*	0.721 **	0.924 ***	0.260
		(0.335)	(0.311)	(0.162)
(14)	*Stay, Old/Ed. in Other*	0.763	0.994	0.132
		(0.964)	(1.067)	(0.530)
(15)	*Stay, Old/Ed./Ten. in Other*	-0.124	-0.008	0.207 *
		(0.256)	(0.274)	(0.108)
(16)	*Stay, Young in R&D*	0.401	0.503	0.033
		(0.327)	(0.361)	(0.148)
(17)	*Stay, Old in R&D*	-0.577	-0.800	-0.246
		(0.431)	(0.552)	(0.256)
(18)	*Stay, Old/Ten. in R&D*	-0.148	0.174	0.279 ***
		(0.213)	(0.224)	(0.095)
(19)	*Sepa, Young from Other*	-0.154	-0.397 **	-0.247 ***
		(0.134)	(0.156)	(0.064)
(20)	*Sepa, Old from Other*	0.599 **	1.040 ***	0.366 ***
		(0.281)	(0.361)	(0.136)
(21)	*Sepa, Old/Ten. from Other*	0.268 *	0.299 *	0.070
		(0.155)	(0.155)	(0.059)
(22)	*Sepa, Young/Ed. from Other*	-1.032	-0.776	0.145
		(0.683)	(0.776)	(0.320)
(23)	*Sepa, Old/Ed. from Other*	1.848	1.851	-0.194
		(1.210)	(1.241)	(0.605)
(24)	*Sepa, Old/Ed./Ten. from Other*	-1.169	-0.689	0.304
		(0.880)	(0.950)	(0.233)
(25)	*Sepa, Young from R&D*	-0.116	0.055	0.158
		(0.569)	(0.644)	(0.280)
(26)	*Sepa, Old from R&D*	0.557	0.839	0.314
		(1.143)	(1.316)	(0.565)
(27)	*Sepa, Old/Ten. from R&D*	0.776	0.604	-0.197
		(0.849)	(0.809)	(0.285)
(28)	*Capital intensity growth*	0.022	0.041 **	0.019 ***
		(0.020)	(0.021)	(0.007)
(29)	*Initial labor productivity*	-0.254 ***	-0.219 ***	0.052 ***
		(0.048)	(0.048)	(0.013)
(30)	*Initial wage sum*	0.428 ***	-0.095	-0.574 ***
		(0.096)	(0.101)	(0.037)
(31)	*Foreign ownership*	0.034	0.042	0.024 *
		(0.034)	(0.036)	(0.014)
(32)	*Firm age*	-0.002	-0.031 *	-0.019 ***
		(0.016)	(0.016)	(0.007)
(33)	*Multi-estabilishment*	-0.036	-0.021	0.009
		(0.024)	(0.024)	(0.010)
Also including industry (41 in all) and regional (20 in all) dummies.				
Observations		1,339	1,339	1,339
R^2		0.50	0.52	0.67

Note: ***, **, and * indicate statistical significance at 1, 5, and 10 per cent levels. Concerns firms with at least 20 persons. Estimated with employment weights. Heteroscedasticity-consistent standard errors in parenthesis.

While the staying and separating variables are primarily controls, it is interesting to note that having a large fraction of staying young educated workers in non-R&D occupations boost productivity and profitability (the young low-educated workers is the reference group here). Furthermore, we find that the separation of certain sub-groups of the older workers has a significant positive effect on productivity and profitability growth, implying that these workers were less productive and profitable than the average worker of the firm.[20] We also find that a higher share of staying older workers has a negative effect on productivity growth (the result for older R&D workers is statistically insignificant, however).[21]

The most important and interesting finding can be read from the 5th and 6th rows of Table 3: we find that hiring R&D workers from other firms has a positive effect on productivity, when they are hired to non-R&D occupations. The estimates also indicate that these workers are very highly paid but, even so, these recruitments are profitable to the company. These findings apply to both young and old workers. On the other hand, no statistically significant effects can be found when workers are hired to R&D occupations, irrespective of the source of these flows.[22]

5. Robustness

As a general remark, we wish to point out that the empirical setup employed in the previous section leads to conservative estimates, i.e. more likely to lead to statistically insignificant results rather than the opposite. From the outset firm-specific effects are removed and the setup is also robust to changes in firm structure. In addition, we control for the possible presence of industry and regional shocks as well as for a host of other factors that could influence profitability and productivity growth.

In this section we perform two robustness checks (cf. Table 4). First, we use a cut-off limit of 10 persons instead of the 20 persons cut-off point used in the baseline regressions in Section 5. With this adjustment our main finding that hiring former R&D workers to non-R&D occupations affects positively profitability remains statistically significant, albeit at a somewhat lower level. We attribute this to the fact that the measurement accuracy is substantially weaker among those additional 713 ($=2{,}052-1{,}339$) firms employing 10–19 persons.[23] Second, in order to study the possible effects of outliers, we estimate a median regression of the model; also these regressions confirm our core finding.

Table 4. OLS regressions with an alternative cut-off limit and median regressions.

		10 persons as the cut-off			Median regression		
		Profitability	*Productivity*	*Wage*	*Profitability*	*Productivity*	*Wage*
(1)	*Hire, Young into Other*	-0.043	-0.075	-0.040	-0.065	-0.287 ***	-0.087
		(0.084)	(0.095)	(0.048)	(0.044)	(0.098)	(0.053)
(2)	*Hire, Old into Other*	-0.188	-0.342 **	-0.154 ***	-0.170 ***	-0.141	-0.162 **
		(0.149)	(0.154)	(0.059)	(0.055)	(0.124)	(0.068)
(3)	*Hire, Young/Ed. into Other*	0.464	0.651 **	0.361 **	0.366 **	1.108 ***	0.338 *
		(0.325)	(0.323)	(0.145)	(0.148)	(0.337)	(0.186)
(4)	*Hire, Old/Ed. into Other*	-0.089	0.311	0.573 **	-0.495 *	-0.430	0.973 ***
		(0.517)	(0.564)	(0.258)	(0.269)	(0.617)	(0.336)
(5)	*Hire, Young/R&D into Other*	2.571 *	3.174 **	0.633	1.624 **	4.182 ***	1.223
		(1.441)	(1.592)	(0.616)	(0.643)	(1.437)	(0.776)
(6)	*Hire, Old/R&D into Other*	2.885 *	3.683 *	1.340 **	1.753 **	3.677 **	0.807
		(1.702)	(1.949)	(0.635)	(0.768)	(1.708)	(0.866)
(7)	*Hire, Young/R&D into R&D*	-0.827	-0.154	0.539 *	-0.420	-0.853	0.165
		(0.972)	(0.989)	(0.324)	(0.474)	(1.048)	(0.568)
(8)	*Hire, Old/R&D into R&D*	1.234	1.122	0.116	-0.031	1.315	0.038
		(0.871)	(0.957)	(0.410)	(0.615)	(1.362)	(0.750)
(9)	*Hire, Young/Ed. into R&D*	-0.384	-0.390	0.208	-0.160	0.035	0.146
		(0.415)	(0.480)	(0.198)	(0.197)	(0.453)	(0.246)
(10)	*Hire, Old/Ed. into R&D*	-0.339	-0.485	-0.167	-0.528 *	-0.266	0.080
		(0.533)	(0.601)	(0.271)	(0.289)	(0.655)	(0.414)
(11)	*Stay, Old in Other*	-0.070	-0.280 **	-0.183 ***	-0.048	-0.191	-0.036
		(0.101)	(0.124)	(0.057)	(0.067)	(0.152)	(0.082)
(12)	*Stay, Old/Ten. in Other*	0.030	0.006	-0.077 **	-0.113 ***	-0.154 *	-0.059
		(0.074)	(0.077)	(0.036)	(0.035)	(0.079)	(0.043)
(13)	*Stay, Young/Ed. in Other*	0.458	0.628 **	0.224 *	0.136	0.115	0.073
		(0.278)	(0.263)	(0.128)	(0.131)	(0.276)	(0.161)
(14)	*Stay, Old/Ed. in Other*	0.972	1.290	0.275	-0.430	0.441	0.053
		(0.757)	(0.865)	(0.395)	(0.368)	(0.822)	(0.430)
(15)	*Stay, Old/Ed./Ten. in Other*	-0.045	0.095	0.209 **	-0.330 ***	-0.302	0.084
		(0.199)	(0.215)	(0.083)	(0.080)	(0.191)	(0.105)
(16)	*Stay, Young in R&D*	0.264	0.356	0.044	0.153	0.026	0.069
		(0.221)	(0.244)	(0.100)	(0.116)	(0.265)	(0.148)
(17)	*Stay, Old in R&D*	-0.368	-0.516	-0.146	-1.078 ***	-0.601	-0.182
		(0.306)	(0.381)	(0.186)	(0.188)	(0.434)	(0.268)
(18)	*Stay, Old/Ten. in R&D*	-0.039	0.241	0.257 ***	-0.005	0.285	0.372 ***
		(0.158)	(0.169)	(0.072)	(0.090)	(0.210)	(0.112)
(19)	*Sepa, Young from Other*	-0.100	-0.287 **	-0.190 ***	-0.135 ***	-0.159	-0.118 **
		(0.106)	(0.127)	(0.052)	(0.047)	(0.107)	(0.057)
(20)	*Sepa, Old from Other*	0.478 **	0.759 **	0.218 *	0.348 ***	0.229	0.013
		(0.242)	(0.328)	(0.116)	(0.115)	(0.250)	(0.141)
(21)	*Sepa, Old/Ten. from Other*	0.253 *	0.274 **	0.051	0.213 ***	0.201 *	0.164 ***
		(0.135)	(0.136)	(0.050)	(0.047)	(0.106)	(0.057)
(22)	*Sepa, Young/Ed. from Other*	-0.532	-0.292	0.179	-0.457 **	-0.928 *	0.318
		(0.529)	(0.595)	(0.242)	(0.214)	(0.500)	(0.264)
(23)	*Sepa, Old/Ed. from Other*	1.077	1.134	-0.084	-0.073	0.541	0.088
		(0.992)	(1.018)	(0.491)	(0.476)	(1.110)	(0.614)
(24)	*Sepa, Old/Ed./Ten. from Other*	-1.045	-0.591	0.286	0.073	1.037 **	0.350
		(0.763)	(0.824)	(0.199)	(0.219)	(0.493)	(0.267)
(25)	*Sepa, Young from R&D*	-0.063	0.081	0.110	-0.570 **	-0.617	0.163
		(0.394)	(0.450)	(0.201)	(0.223)	(0.516)	(0.275)
(26)	*Sepa, Old from R&D*	0.551	0.746	0.205	1.767 ***	1.278	0.607
		(0.840)	(0.993)	(0.438)	(0.400)	(0.930)	(0.589)
(27)	*Sepa, Old/Ten. from R&D*	0.502	0.459	-0.071	0.060	0.513	-0.389
		(0.623)	(0.598)	(0.218)	(0.300)	(0.701)	(0.335)
(28)	*Capital intensity growth*	0.022	0.041 **	0.019 ***	0.022	0.041 **	0.019 ***
		(0.020)	(0.021)	(0.007)	(0.020)	(0.021)	(0.007)
(29)	*Initial labor productivity*	-0.254 ***	-0.219 ***	0.052 ***	-0.254 ***	-0.219 ***	0.052 ***
		(0.048)	(0.048)	(0.013)	(0.048)	(0.048)	(0.013)
(30)	*Initial wage sum*	0.428 ***	-0.095	-0.574 ***	0.428 ***	-0.095	-0.574 ***
		(0.096)	(0.101)	(0.037)	(0.096)	(0.101)	(0.037)
(31)	*Foreign ownership*	0.034	0.042	0.024 *	0.034	0.042	0.024 *
		(0.034)	(0.036)	(0.014)	(0.034)	(0.036)	(0.014)
(32)	*Firm age*	-0.002	-0.031 *	-0.019 ***	-0.002	-0.031 *	-0.019 ***
		(0.016)	(0.016)	(0.007)	(0.016)	(0.016)	(0.007)
(33)	*Multi-estabilishment*	-0.036	-0.021	0.009	-0.036	-0.021	0.009
		(0.024)	(0.024)	(0.010)	(0.024)	(0.024)	(0.010)
Also including industry (41 in all) and regional (20 in all) dummies.							
Observations		2,052	2,052	2,052	1,397	1,397	1,397
R^2		0.48	0.49	0.64	–	–	–

Note: ***, **, and * : statistical significance at 1, 5, and 10 per cent levels. Estimated with employment weights.

6. CONCLUSION

This paper has used linked employer-employee firm- and individual-level data to test for the existence of labor flows as a source of knowledge spillovers. While there exists a large number of studies that estimate and conclude to the existence of spillovers, most of them are unable to dissociate knowledge from rent spillovers, and very few come to grips with the channels of knowledge spillovers. Potential channels are assumed and used to construct indexes of R&D spillovers, giving more weight to outside R&D sources that correspond to large flows through a presumed channel of transmission (e.g. import of machineries, trade of intermediate inputs, extent of R&D collaborative research to name only a few). We have tried to isolate a particular channel and test whether that channel does indeed carry signs of knowledge spillovers. More precisely, we have tested whether productivity growth in our representative sample of Finnish firms was correlated with the hiring of workers that had worked in R&D departments in their previous employment, and whether or not any additional productivity performance due to the hiring of these workers was not captured by higher wages, i.e. resulted in higher profitability.

There is quite strong evidence of firm-to-firm knowledge spillovers but not of the most obvious type. Hiring workers from other R&D labs to one's own does not seem to be a statistically significant spillover channel, even if we do find weak support for it.[24] Hiring workers previously engaged in R&D to one's non-R&D activities, however, clearly boosts both productivity and profitability. This is interpreted as evidence that these workers transmit knowledge that can be readily copied and implemented without much additional R&D effort. Our findings also suggest that knowledge spillovers associated with R&D and channeled through inter-firm labor mobility may be partly, but are not fully, internalized by the labor market. Thus, inter-firm labor mobility is indeed found to be a channel of knowledge spillovers.

To the best of our knowledge, this is one of the first papers that isolates and estimates the performance effects of R&D-related knowledge spillovers transmitted through inter-firm labor mobility. Even if we study a specific type and transmission channel of spillovers, it should not be taken as an indication that we see other types and channels any less important. Our analysis was conducted at the level of the firm; an interesting avenue for further research would be to study the transmission of knowledge at the level of the employee.

Appendix: Derivation of equation (5)

$$\begin{aligned}
&\sum_j^M \frac{L_{1j,stay}}{L_1}\frac{Y_{1j,stay}}{L_{1j,stay}} + \sum_j^M \frac{L_{1j,hire}}{L_1}\frac{Y_{1j,hire}}{L_{1j,hire}} \\
&= \left(\frac{1}{\sum_j L_{1j,stay}}\right)\sum_j^M L_{1j,stay}\left(\frac{1}{L_1}\right)\sum_j^M L_{1j,stay}\frac{Y_{1j,stay}}{L_{j,stay}} + \sum_j^M \frac{L_{1j,hire}}{L_1}\frac{Y_{1j,hire}}{L_{1j,hire}} \\
&= \sum_j^M \frac{L_{1j,stay}}{\sum_j L_{1j,stay}}\frac{Y_{1j,stay}}{L_{1j,stay}}\sum_j^M \frac{L_{1j,stay}}{L_1} + \sum_j^M \frac{L_{1j,hire}}{L_1}\frac{Y_{1j,hire}}{L_{1j,hire}} \\
&= \sum_j^M \frac{L_{1j,stay}}{\sum_{1j} L_{1j,stay}}\frac{Y_{1j,stay}}{L_{1j,stay}}(1-\sum\frac{L_{1j,hire}}{L_1}) + \sum_j^M \frac{L_{1j,hire}}{L_1}\frac{Y_{1j,hire}}{L_{1j,hire}} \\
&= \sum_j^M \frac{L_{1j,stay}}{\sum_{1j} L_{1j,stay}}\frac{Y_{1j,stay}}{L_{1j,stay}} - \sum_j^M \frac{L_{1j,stay}}{\sum_{1j} L_{1j,stay}}\frac{Y_{1j,stay}}{L_{1j,stay}}\sum\frac{L_{1j,hire}}{L_1} + \sum_j^M \frac{L_{1j,hire}}{L_1}\frac{Y_{1j,hire}}{L_{1j,hire}} \\
&= \sum_j^M \frac{L_{1j,stay}}{\sum_{1j} L_{1j,stay}}\frac{Y_{1j,stay}}{L_{1j,stay}} + \sum\frac{L_{1j,hire}}{L_1}\left(\frac{Y_{1j,hire}}{L_{1j,hire}} - \sum_j^M \frac{L_{1j,stay}}{\sum_{1j} L_{1j,stay}}\frac{Y_{1j,stay}}{L_{1j,stay}}\right) \\
&= \sum_j^M \frac{L_{1j,stay}}{\sum_{1j} L_{1j,stay}}\frac{Y_{1j,stay}}{L_{1j,stay}} + \sum_j^M \frac{L_{1j,hire}}{L_1}\left(\frac{Y_{1j,hire}}{L_{1j,hire}} - \frac{Y_{1,stay}}{L_{1,stay}}\right)
\end{aligned}$$

where $Y_{1,stay} = \sum_j Y_{1j,stay}$ and $L_{1,stay} = \sum_j L_{1j,stay}$.

References

Ali-Yrkkö, J., and Maliranta, M., 2006. Impact of R&D on Productivity; Firm-level Evidence from Finland. *ETLA Discussion Papers, 1031*.

Almeida, P., and Kogut, B., 1999. Localization of Knowledge and the Mobility of Engineers in Regional Networks. *Management Science, 45*(7), 905–917.

Arrow, K. J., 1962. Economic Welfare and the Allocation of Resources for Invention. In R. R. Nelson (Ed.), *The Rate and Direction of Inventive Activity: Economic and Social Factors* (pp. 609-626). Princeton: Princeton University Press.

Becker, G. S., 1962. Investment in Human Capital: A Theoretical Analysis (Part 2: Investment in Human Beings). *Journal of Political Economy, 70*(5), 9–49.

Breschi, S., and Lissoni, F., 2001. Knowledge Spillovers and Local Innovation Systems: A Critical Survey. *Industrial and Corporate Change, 10*(4), 975–1005.

Combes, P.-P., and Duranton, G., 2006. Labour Pooling, Labour Poaching, and Spatial Clustering. *Regional Science and Urban Economics, 36*, 1–28.

Cooper, D. P., 2001. Innovation and Reciprocal Externalities: Information Transmission via Job Mobility. *Journal of Economic Behavior & Organization, 45*(4), 403–425.

Diewert, W. E., and Fox, K. A., forthcoming. On Measuring the Contribution of Entering and Exiting Firms to Aggregate Productivity Growth. In W. E. Diewert, B. M. Balk, D. Fixler, K. J. Fox & A. Nakamura (Eds.), *Index Number Theory and the Measurement of Prices and Productivity* (forthcoming). Victoria: Trafford Publishing.

Fallick, B., Fleischman, C. A., and Rebitzer, J. B., 2006. Job-Hopping in Silicon Valley: Some Evidence Concerning the Microfoundations of a High-Technology Cluster. *Review of Economics and Statistics, 88*(3), 472–481.

Fosfuri, A., and Rønde, T., 2004. High-Tech Clusters, Technology Spillovers, and Trade Secret Laws. *International Journal of Industrial Organization, 22*(1), 45–65.

Franco, A. M., and Filson, D., 2006. Spin-Outs: Knowledge Diffusion through Employee Mobility. *RAND Journal of Economics, 37*(4), 841–860.

Friedman, M., 1992. Do Old Fallacies Ever Die? *Journal of Economic Literature, 30*(4), 2129–2132.

Geroski, P. A., 1995. Do Spillovers Undermine the Incentive to Innovate? In S. Dowrick (Ed.), *Economic Approaches to Innovation* (pp. 76–97). Aldershot, UK: Edward Elgar.

Griliches, Z., 1992. The Search for R&D Spillovers. *Scandinavian Journal of Economics, 94*(Supplement), 29–47.

Griliches, Z., and Mairesse, J., 1998. Production Functions: The Search for Identification. In R. Strøm (Ed.), *Econometrics and economic theory in the twentieth century: The Ragnar Frisch Centennial Symposium* (pp. 169–203). Cambridge; New York and Melbourne: Cambridge University Press.

Hadi, A. S., 1992. Identifying Multiple Outliers in Multivariate Data. *Journal of the Royal Statistical Society, Series (B), 54*, 761–771.

Hadi, A. S., 1994. A Modification of a Method for the Detection of Outliers in Multivariate Samples. *Journal of the Royal Statistical Society, Series (B), 56*, 393–396.

Hellerstein, J. K., and Neumark, D., 2004. Production Function and Wage Equation Estimation with Heterogeneous Labor: Evidence from a New Matched Employer-Employee Data Set. *NBER Working Papers, 10325*.

Ilmakunnas, P., and Maliranta, M., 2005. Worker Inflow, Outflow, and Churning. *Applied Economics, 37*(10), 1115–1133.

Ilmakunnas, P., and Maliranta, M., 2007. Aging, Labor Turnover and Firm Performance. *ETLA Discussion Papers, 1092*.

Kim, J., and Marschke, G., 2005. Labor Mobility of Scientists, Technological Diffusion, and the Firm's Patenting Decision. *RAND Journal of Economics, 36*(2), 298–317.

Levinsohn, J., and Petrin, A., 2003. Estimating Production Functions Using Inputs to Control for Unobservables. *Review of Economic Studies, 70*(2), 317-341.

Magnani, E., 2006. Is Workers' Mobility a Source of R&D Spillovers? Evidence of Effects of Innovative Activities on Wages. *International Journal of Manpower, 27*(2), 169–188.

Maliranta, M., 1997. Plant-level explanations for the catch-up process in Finnish manufacturing: A decomposition of aggregate labour productivity growth. In S. Laaksonen (Ed.), *The Evolution of Firms and Industries. International Perspectives* (pp. 352–369). Helsinki: Statistics Finland.

Maliranta, M., 2003. *Micro Level Dynamics of Productivity Growth. An Empirical Analysis of the Great Leap in Finnish Manufacturing Productivity in 1975–2000*. Helsinki: Taloustieto Oy.

Marschak, J., and Andrews, W. H., 1944. Random Simultaneous Equations and the Theory of Production. *Econometrica, 12*(3, 4), 143–205.

Mincer, J., 1958. Investment in Human Capital and Personal Income Distribution. *Journal of Political Economy, 66*(4), 281-302.

Mohnen, P. A., 1996. R&D Externalities and Productivity Growth. *STI review*, *18*, 39–66.

Møen, J., 2005. Is Mobility of Technical Personnel a Source of R&D Spillovers? *Journal of Labor Economics, 23*(1), 81–114.

Nelson, R. R., and Phelps, E. S., 1966. Investment in Humans, Technological Diffusion, and Economic Growth. *American Economic Review Papers and Proceedings LVI*, 69–75.

Olley, G. S., and Pakes, A., 1996. The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica, 64*(6), 1263–1297.

Power, D., and Lundmark, M., 2004. Working through Knowledge Pools: Labour Market Dynamics, the Transference of Knowledge and Ideas, and Industrial Clusters. *Urban Studies, 41*(5-6), 1025–1044.

Rouvinen, P., 2002. R&D-productivity dynamics: Causality, lags, and 'dry holes'. *Journal of Applied Economics, 5*(1), 123–157.

Stephan, P. E., 1996. The Economics of Science. *Journal of Economic Literature, XXXIV*(3), 1199–1235.

Vainiomäki, J., 1999. Technology and Skill Upgrading: Results from Linked Worker-Plant Data for Finnish Manufacturing. In J. Haltiwanger, J. Lane, J. R. Spletzer, J. J. M. Theuwes & K. R. Troske (Eds.), *The creation and analysis of employer-employee matched data* (pp. 115–145). Amsterdam; New York and Oxford: Elsevier Science, North-Holland.

White, H., 1980. A Heteroscedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroscedasticity. *Econometrica, 48*(4), 817–838.

Endnotes

[1] Please contact the Research Laboratory of the Business Structures Unit, Statistics Finland, FIN-00022, Finland, for accessing the data.

[2] Also Maliranta (1997), Vainiomäki (1999), and Diewert and Fox (forthcoming) have proposed similar decompositions.

[3] The Nelson–Phelps (1966) effect.

[4] This measure of profitability may seem rather rough as capital costs are not taken into account. Note, however, that our empirical implementation removes time-invariant firm-effects, includes industry dummies, and – most importantly – controls for change firms' capital intensities.

[5] Instrumental variables (IV) is an inefficient estimator that requires a large number of observations and a large set of appropriate instruments when the model includes many potentially endogenous variables. In a similar context Ilmakunnas and Maliranta (2007) have 16,389 observations in their estimations but we have only 1,339 observations in our baseline models, which substantially restricts our opportunities to use the IV-method. More importantly, Ilmakunnas and Maliranta have only 6 potentially endogenous hiring and separation variables; in our analysis the corresponding number is 19. Thus, due to data and coefficient dimensions as well as weak instruments, similar approach is not feasible here.

IV-method is an inefficient estimator that requires a large number of observations and a large set of appropriate instruments when the model includes many potentially endogenous variables.

[6] It is worth noting, however, that while our explanatory variables include all hiring and separating flows, we are implicitly controlling for the net employment growth (jointly determined by hiring and separating flows) that is one of the apparent consequences of a technology shock. Moreover, our set of explanatory variables includes a wide array of factors, including detailed industry and regional dummies, which should eliminate any remaining bias.

[7] FLEED has data on both firms and establishments. While in many contexts the establishment level is appealing for both theoretical and empirical reasons, in the current context it is not. In the case of a multi-establishment firm (in other cases the establishment and firm levels coincide), an establishment is rarely the relevant decision making unit when it comes to R&D. Furthermore, firm-level R&D efforts are often more concentrated than production and possible discoveries are spread through the firm, in which case plant-level investments in R&D and related performance effect may have a rather noisy connection. Thus our analysis progresses at the level of a firm.

[8] Assuming homogenous individuals and no time lags in their performance effects, one could think of all (or "average") hiring and separating as taking place in mid-1998.

[9] For both the stayers and separating workers the "maintained" job assignment (either in R&D or in Other (non-R&D) activities in the initial period) is indicated in the middle column of Table 1.

[10] Code 32 in *Statistic Finland*'s 1989 classification of socio-economic groups.

[11] Those in R&D tasks are assumed to be highly educated or to have similar qualifications. The hires with no tenure at the firm are labeled as having a short tenure. Note that by including the hiring, staying, and separating variables we implicitly control for the level and changes in all the dimensions considered. Thus, for example, the firm's R&D intensity and changes in it are implicitly controlled for via the labor shares.

[12] Note that the start- and end-year employment is the same for staying by definition, and that the shares add up to one; thus the comparison group *Stay, Young, in Other* is necessarily excluded from the regressions.

[13] Thus, the measures may be considered as reflecting the rate of change/growth in performance at the turn of 1998 and 1999.

[14] This is a relatively standard practice in the growth literature. Note that, by also including industry dummies, this practice captures, among other things, the difference between the firm's and its industry's productivity levels. These variables are included purely as controls – their coefficients should be interpreted with caution.

[15] In practice this means that the firm must have been recorded in 1995, 1996, 2000, and 2001.

[16] Banking and insurance is excluded, as value added is not available for the firms in the industry.

[17] The method is useful for detecting multiple outliers in multivariate data. Identification of outliers is made on the basis of four variables: 1) the growth rate of average wage calculated from the company data, 2) the

productivity growth rate, 3) the growth rate of employment according to the company data, and 4) the growth rate of employment according to the Employment Statistics. In this way we found 73 outliers (out of 2,143 observations at this stage) that were excluded in the baseline estimations (but were nevertheless included in some robustness checks).

[18] Productivity, wage and profitability numbers used in the analysis originate from the Financial Statements Statistics.

[19] Note too, that labor productivity *per se* is not a function of wages unlike a somewhat popular misconception suggests.

[20] Young staying workers with university degrees have a more positive effect on productivity and profitability growth than young or old staying workers without university degrees. In this respect these results bear some resemblance with those of Maliranta (2003, chapter 6) who find evidence of the dynamic effect (or Nelson–Phelps effect) high education.

[21] The results concerning the staying and separated older workers are quite consistent with those by Ilmakunnas and Maliranta (2007).

[22] Note, however, that the *Hire, Old/R&D into R&D* type of workers has a positive and significant at 15% level coefficient on profitability growth.

[23] Increasing the cut-off to 50 persons has the reverse effect, even if the number of observations drops to 599. Using unweighted as opposed to weighted regression has a similar effect, which also suggests that there might be measurement issues at the small end.

[24] In the baseline regression this spillover channel is statistically significant at 15% level but, as it does not seem to be robust to changes in the data and empirical specification, we lean towards accepting the null hypothesis. A possible explanation for this (non-)finding is that the implicit average time-span of 2.5 years in our analysis is too short for a positive effect to occur in the firm's performance. For example, Ali-Yrkkö and Maliranta (2006) show with a panel data set of Finnish firms over the period 1996–2004 that an economically and statistically significant effect cannot be found earlier than three to five years after the R&D investments. Rouvinen (2002) finds support to such a lag with a cross-country industry-level panel.

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